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Impact of climate change on water resources of upper Kharun catchment in Chhattisgarh, India

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ABSTRACT

Study region: The Upper Kharun Catchment (UKC) is one of the most important, economically sound and highly populated watersheds of Chhattisgarh state in India. The inhabitants strongly depend on monsoon and are severely prone to water stress.

Study focus: This research aims to assess the impact of climate change on water balance components.

New hydrological insights for the region: The station-level bias-corrected PRECIS (Providing REgional Climates for Impact Studies) projections generally show increasing trends for annual rainfall and temperature. Hydrological simulations, performed by SWAT (Soil and Water Assessment Tool), indicate over-proportional runoff-rainfall and under-proportional percolation-rainfall relationships. Simulated annual discharge for 2020s will decrease by 2.9% on average (with a decrease of 25.9% for q1 to an increase by 23.6% for q14); for 2050s an average increase by 12.4% (17.6% decrease for q1 to 39.4% increase for q0); for 2080s an average increase of 39.5% (16.3% increase for q1 to an increase of 63.7% for q0). Respective ranges on percolation: for 2020s an average decrease by 0.8% (12.8% decrease for q1 to an increase of 8.7% for q14); for 2050s an average increase by 2.5% (10.3% decrease for q1 to 15.4% increase for q0); for 2080s an average increase by 7.5% (0.3% decrease for q1 to 13.7% increase for q0). These over- and under-proportional relationships indicate future enhancement of floods and question sufficiency of groundwater recharge.

Abbreviations: ARS, Agricultural Research Service; ZEF, Center for Development Research; CGCOST, Chhattisgarh Council of Science and Technology; GCM, General Circulation Model; DAAD, German Academic Exchange Service; IITM, Indian Institute of Tropical Meteorology; IMK-IFU, Institute of Meteorology and Climate Research; IPCC, Intergovernmental Panel on Climate Change; KIT, Karlsruhe Institute of Technology; NDVI, Normalized Difference Vegetation Index; PRECIS, Providing Regional Climates for Impact Studies; RCM, Regional Climate Model; SWAT, Soil and Water Assessment Tool; USDA, United States Department of Agriculture; UKC, Upper Kharun Catchment

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1. Introduction

According to the Intergovernmental Panel on Climate Change (IPCC AR5, 2014), the global mean temperature may increase up to 4 °C by 2100, and will severely affect the availability of water resources and the water demand across the world. The combined effect on the water supply and the demand side is expected to increase supply-demand gaps in tendency, which in turn is exacerbating the current challenges of water management.

Climate change will likely affect the surface and groundwater resources due to the expected changes in precipitation and evapotranspiration and the spatio-temporal distribution of these essential water balance components (Garner et al., 2017; Kirby et al., 2016; Bear et al., 1999). Increased intensities of precipitation will lead to higher rates of surface runoff, an increased risk of flood and decreased rates of groundwater recharge (Trenberth, 2011). A rise in temperature causes higher evapotranspiration, and, in turn, further enhances the demand for irrigation water, by far already the biggest water consumer under present conditions (Wang et al., 2012). In order to enable water management to cope with future challenges, the impact of climate change on the water balance needs to be quantified from regional to local (basin) scales. Research activities during the last decades increasingly address this issue.

General Circulation Models (GCMs) are often used for understanding the climate dynamics and projecting future climate change. They can provide input data for climate change impact studies on coarse horizontal scales (typically in the order of 100–300 km). This resolution, however, is still too coarse for any regional or local scale climate change impact studies. For obtaining the climate variables on regional scale, the projections of climate variables need be downscaled from the GCM resolution, utilizing either dynamical or statistical methods (IPCC, 2001). Downscaling by a dynamical approach using a regional climate model (RCM) delivers physically consistent climate variable (usually horizontal resolutions of 5–50 km). However, even high-resolution RCM output is still prone to systematic errors (biases) compared to point observations. Therefore, bias corrections are often applied to RCM simulations to study the impact of climate change on the hydrology of a basin by hydrological models.

In literature, several bias correction methodologies of different complexity have been developed (e.g., Sippel et al., 2016; Berg et al., 2012; Bordoy and Burlando, 2013; Haerter et al., 2011; Piani et al., 2010; Terink et al., 2010). All of them derive a transfer function between the large scale climate information from GCM (or RCM) scales and local scales. These transfer functions are then applied for the future climate projections under the assumption of stationary conditions. Current bias correction methods range from simple linear methods e.g. (Hay et al., 2000; Lenderink et al., 2007) via statistical distribution-based algorithms e.g. (Themeßl et al., 2011; Piani et al., 2010) towards Copulas, which are able to consider complex dependence structures and allow a dynamic correction (e.g., Laux et al., 2011; Mao et al., 2015).

Climate change is evident in Indian sub-continent. Numerous studies have predicted an increasing trend in annual surface temperature (Rupa Kumar et al., 1994; Pant et al., 1999; Singh and Sontakke, 2002; Subash and Sikka, 2014) and a significant decreasing/increasing trend in rainfall at different regional and local scale in India (Chaudhary and Abhyankar, 1979; Srivastava et al., 1998; Kumar et al., 2005; Kumar et al., 2010; Adarsh and Janga Reddy, 2015). Throughout the 21st century, it is projected that India and Southeast Asian countries will face more warming than the global mean and there will be greater variations in temperature, with higher warming rates in winter than in summer in India (Christensen et al., 2007). Bhadwal (2003) reports about an increased variability in summer monsoon precipitation, which may severely affect water resources and may cause drastic losses in the agricultural sector. Dash et al. (2007) reported of a decreasing trend in monsoon rainfall and an increasing trend in pre- and post-monsoon periods based on rainfall time series data from 1871 to 2002. Guhathakurta and Rajeevan (2008) performed monthly rainfall observations for linear trends across 36 climatological regions (representing different parts of India) during the period 1901–2003. They found significant decreases in monsoon rainfall for Jharkhand, Chhattisgarh and Kerala, whereas 8 regions showed significant increases.

A number of studies have assessed the impact of climate change projections on the hydrology of various regions throughout the world (e.g., Dragoni, 1998; Buffoni et al., 2002; Labat et al., 2004; Huntington, 2006; IPCC, 2007). However, process-based studies for catchments in India are scarce; some of them applied the Soil and Water Assessment Tool (SWAT) model (e.g., Kulkarni et al., 2014; Dhar and Mazumdar, 2009; Gosain et al., 2006).

India's freshwater resources are mainly generated by the southwest monsoon. As a consequence, fulfilling water requirements for agriculture, industries, domestic purposes, energy sectors and ecosystems depends on the monsoonal system. More than 80% of the annual rainfall occurs during the monsoon period i.e., between June-September (Kumar et al., 2010). Therefore, any change in the climate, in particular during the Indian southwest monsoon would have a significant impact on the agricultural production, which is already now under stress due to high population growth rates and problems related to water resources management (Mall et al., 2006). In spite of the uncertainties about the precise magnitude of climate change and its possible impacts (particularly on regional scales) measures must be taken to anticipate, prevent or minimize its adverse effects on water availability. Understanding the impacts of climate change (based on scenarios) on water balance components requires hydrological modeling and one such hydrological model used in this study is Soil and Water Assessment Tool (SWAT). A detailed description of SWAT model and the reasons for its selection in this study are discussed in methodology section (3.3).

The Upper Kharun Catchment (UKC) features considerable population growth and dynamic changes in irrigation practices (extension, intensification) for meeting the increasing food demand. It is expected that the impacts of future climate change will be severe in the UKC, because its economy largely depends on agriculture. In spite of the uncertainties about the precise magnitude of climate change and its possible impacts, particularly on regional and local scales, measures must be taken to prevent or minimize the impacts of climate change and mitigate and/or adapt to its adverse effects on surface and groundwater availability.

Current analyses do not sufficiently address the impact of climate change and their interactions with water resources in UKC. Hence, considering the above facts, the overall aim of this research is to investigate the potential impacts of climate change on the water resources of the Upper Kharun Catchment, India using bias corrected PRECIS RCM projections in combination with the Soil and Water Assessment Tool (SWAT). The results may contribute to enhance our understanding of climate change and its potential impacts on water balance components in the region, which may finally facilitate the improvement of water management practices. We are not aware of any study tackling the impact of climate change on the hydrology of the Kharun basin. The scientific innovation of this paper consists in a better description of the land use map by combining different intra-seasonal crop rotation dynamics and crop type within a single map as well as the irrigation amounts based on sources and per land use type, have been included as spatially explicit information in the SWAT model.

2. Study area

The study area is the Upper Kharun Catchment (UKC), which is a part of the Seonath sub-basin (a tributary of Mahanadi river basin) and the state Chhattisgarh, formed in 2000. It covers an area of 2486 km^2. UKC features considerable a population growth of about 2.62%, urbanization (increase by 2 times between 1991 and 2011), industrialization (increase by 3 times between 1991 and 2011), and dynamic changes in irrigation practices especially towards raising groundwater withdrawals for extension and intensification of irrigation in order to meet the increasing food demand.

In terms of administrative units, the UKC is located in parts of Raipur, Durg and Dhamtari districts of Chhattisgarh state, India. It lies between 20°33′ 30″ N–21°22′ 05″ N latitude and 81°17′ 53″ E–81° 45′ 17″ E longitude (Fig. 1). UKC is situated in Chhattisgarh Plains Zone, and experiences three typical Indian seasons, namely winter (mid-October to mid-February), summer (mid-February to mid-June) and monsoon (mid-June to mid-October). The climate is tropical and average annual rainfall is in the range of 1100 mm.

UKC is considered as one of the most important, economically sound and highly populated catchments of Chhattisgarh state. Raipur is the capital city and the most developed district followed by Durg and Dhamtari districts. The UKC covers diverse land-use types, i.e., urban (3.6%), rural (4.2%), agricultural (77.6%), forest (5.3%), industrial areas (0.7%), wasteland (6.9%) and water bodies (1.7%) Most of the study area is agricultural land with 514 villages. The main crop grown in the area is paddy (rice). Four major soil types are found in the UKC namely, Alfisols (loam also known as Dorsa), Vertisols (clay also known as Kanhar), Entisols (sandy loam also known as Bhata) and Inceptisols (sandy clay loam also known as Matasi) (source: State data centre, Raipur).

3. Methodology

In the following, the applied climate hydrological modeling chain as well as the data used in this study are described.

3.1. Methodological approach and major data sets

The impact of climate change on water resources was studied in terms of surface runoff, discharge, actual evapotranspiration, groundwater recharge and groundwater contribution to streamflow in the UKC, which were simulated by the *Soil and Water Assessment Tool*, subsequently referred to as SWAT model (Arnold et al., 1998). Fig. 2 illustrates the applied climate hydrological modeling chain.

The following major input data sets were collected, compiled and used. A more comprehensive overview about the different data sources used in this study is given in the supplementary file S1.

1 Observed climate data: 13 rainfall stations and one meteorological station (Raipur) are available in and around the study area (Fig. 3). At the rainfall stations, daily rainfall was measured during the period 1990–2011. Some of the 13 stations are slightly affected by missing value. Such data gaps (at some stations mostly occurring during 1990–2000) were filled using the averaging of nearby rainfall station values. At the meteorological station, time series of daily rainfall (mm), minimum and maximum temperature (°C), relative humidity (%), actual sunshine duration (hours) and wind speed (km/h) data were available from 1971 to 2011 without any data gap. These data at daily time steps were obtained from the *State Data Centre, Department of Water Resources, Raipur, Council of Science and Technology, Raipur* and the *Indian Meteorological Department,* Pune (Source: http://www.imdpune.gov.in/ndc_new/Request.html and http://hydrologyproject.cg.gov.in/State%20Data%20Center/state_data_center.htm).
2 Soil map: A detailed soil map with 64 soil attribute types was scaled to 1:50,000. Field surveys, reports of soil survey departments and previous soil map (Fig. 4a) provided by National Bureau of Soil Survey and Land Use Planning, Nagpur and state data center, Raipur (source: https://www.nbsslup.in/) were used to develop the detailed soil map. The soil physical properties required for running SWAT model were estimated, following the approach of point pedotransfer (using Baumer method) for estimating permanent wilting point, field capacity and bulk density, and retention function pedotransfer (using Campbell method) for estimating the saturated hydraulic conductivity using *SOILPAR2 software* See further details in Acutis and Donatelli (2003).
3 Land-use map: Satellite imageries LANDSAT images from 3 different typical Indian seasons, i.e. summer, monsoon season and winter of 2011 (source: https://earthexplorer.usgs.gov/), remote sensing techniques, field surveys and census book reports were employed to prepare a detailed land-use map with 19 specific classes for 2011 (Fig. 4b). On screen visual digitization technique with the aid of different vegetation indices (Normalized Difference Vegetation Index (NDVI), Tasseled cap indices (Brightness index, Greenness index and Wetness index)) and band combinations was applied to capture the information from 3 different seasons of 2011. Later the information were integrated to capture the intra-seasonal variation within a year in a single map and hence better represent an area with multiple crop rotations and different levels of urbanization. The definition of different land-use classes was adopted from the technical manual on "National Land Use Land Cover Mapping using multi-temporal satellite

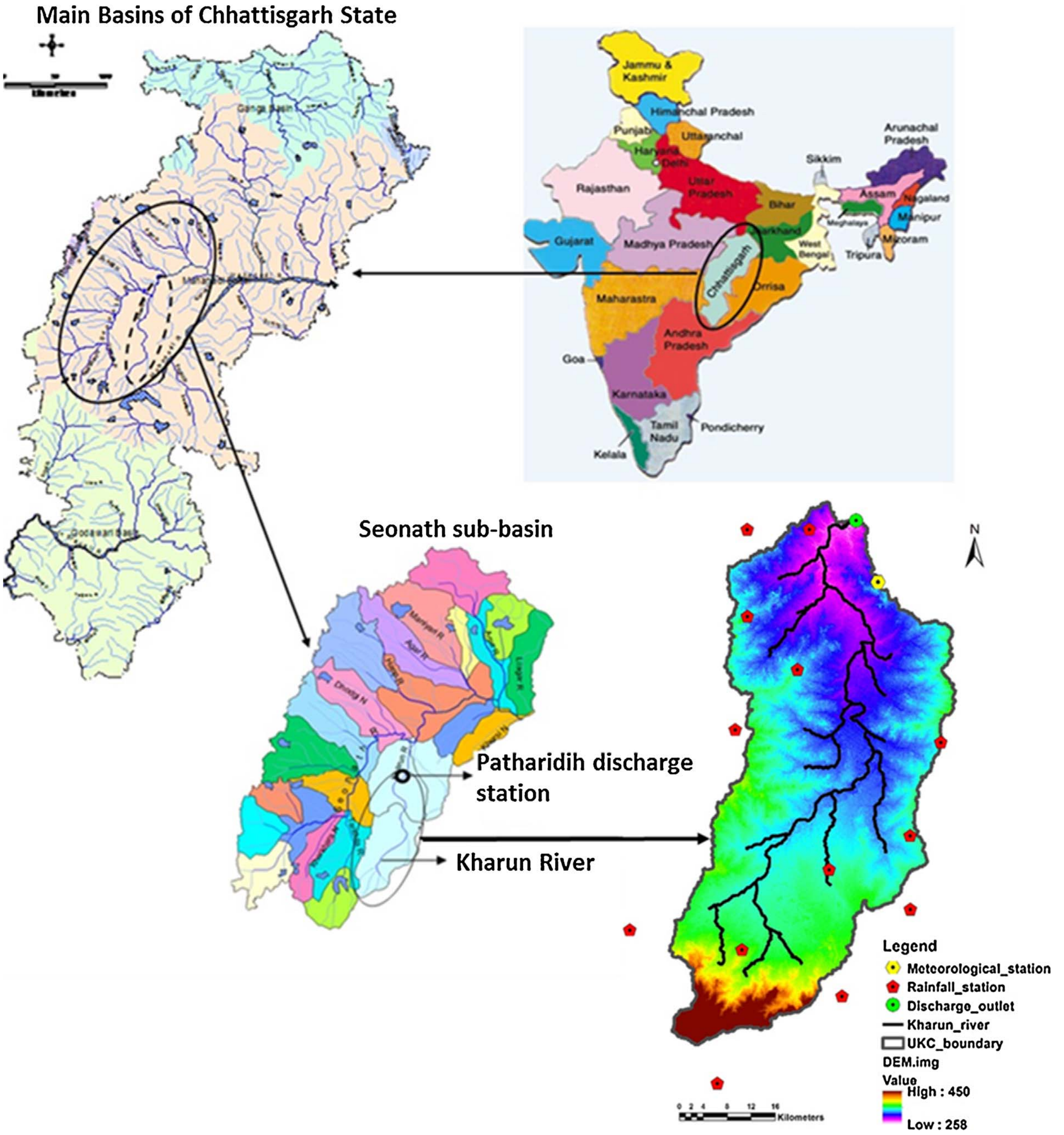


Fig. 1. Upper Kharun Catchment: geographical location, rainfall stations (13), meteorological station (1), discharge outlet (1), Kharun River and SRTM Digital Elevation Model (elevation difference 192 m from south to north).

data" (2012) prepared by the Land Use and Cover Monitoring Division Land Resources, Land Use Mapping and Monitoring Group, National Remote Sensing Centre, Indian Space Research Organization, India and presented in Table 1. Introducing detailed categories and shaping/defining the detailed categories were performed and guided by paying special attention to factors with relevance to the magnitude of hydrological processes (cropping pattern, rainfed/irrigated agriculture areas), because this improves the influential input data and in turn the quality of input for the hydrological model (SWAT).

4 Crop rotation information: In the UKC, three different crop growing seasons are practiced. Depending on the water availability, farmers produce one to three crops in a year. The information about crop rotation and types of crops grown in 2011 was gathered from field visits and block administrative agriculture offices and integrated in the land use map.

Crop types: Paddy is grown as a single major crop in monsoon season, when there is sufficient rainfall supplemented by canal

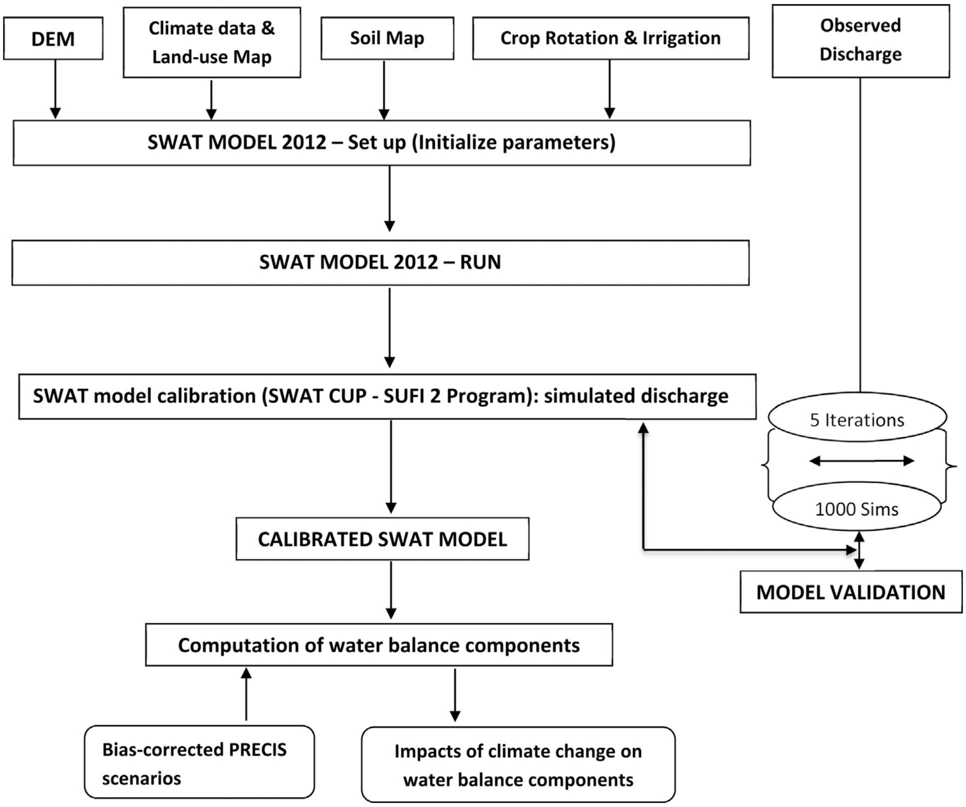


Fig. 2. Flow diagram of climate hydrological modeling chain.

irrigation. Paddy is also taken as 2 or 3 times a year depending on the location in case sufficient groundwater is available for irrigation. Apart from paddy, wheat, chick pea, lentils and vegetables are grown as a second crop.

5 Irrigation: Irrigation water in the UKC is supplied by a well-developed network of canal systems and groundwater sources. Visual interpretation of Landsat satellite imageries and canal index map provided by Raipur irrigation department were used to map the irrigated areas in ArcGIS 10.1. Canal systems are only operated in late monsoon and post monsoon season (September-November) for 2–3 months depending on the water demand. Whereas the crop water demand in other seasons is mostly met by groundwater sources. These sites can be detected by the satellite imageries. This information forms the basis for differentiating the surface and groundwater irrigated areas. Detailed information on the amount of irrigation water supplied by different sources (village-wise census book record, irrigation departments and block agriculture offices) was collected and used as an input into the SWAT model.
6 Digital Elevation Model (DEM): version 4.0 of SRTM DEM with 90-m resolution was used (Source: http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1).
7 Discharge: The discharge from the UKC is measured at Patharidih gauge-discharge site and recorded on a daily basis (8:00 am). The velocity of flow across the cross section of the Kharun River is measured by a current meter (m/s) and the discharge (m^3/s) is estimated using the velocity-area method. Discharge data (based on water level observation in combination with rating curves) from 1989 to 2008 (daily resolution) were obtained from the Central Water Commission, Bhubaneswar, Orissa and were used in model calibration and validation. The discharge is very low from January onwards, and in the Indian summer season (mid-February till mid-June) the Kharun River generally dries up mostly. The average annual discharge (1990–2008) is 1088 million m^3 (source: http://www.cwc.nic.in/regionaloffices/welcome-mero.html).
8 Climate projections: PRECIS (Providing REgional Climates for Impact Studies) regional climate projections for the period 1961–2098 based on 3 different physics parameterizations (q0, q1 and q14) in a horizontal grid resolution of 50 km, have been applied (source: http://www.tropmet.res.in/). Climate variables including precipitation, temperature, wind speed and relative humidity were provided by the Indian Institute of Tropical Meteorology (IITM), Pune, India (Fig. 3).

The three selected members (q0, q1, and q14), pre-selected out of a 17-member perturbed HadCM3 physics ensemble of the A1 B scenario (produced in the project *Quantifying Uncertainty in Model Predictions* project QUMP of Hadley Centre Met Office, UK) have been used as lateral boundary conditions to drive the regional climate model PRECIS. The perturbed physics approach was developed in response to the call for better quantification of uncertainties in climate projections (IPCC, Fourth Assessment Report AR4, 2007). The selection of the A1 B scenario (corresponding to the business-as-usual scenario) for downscaling is based on the data availability

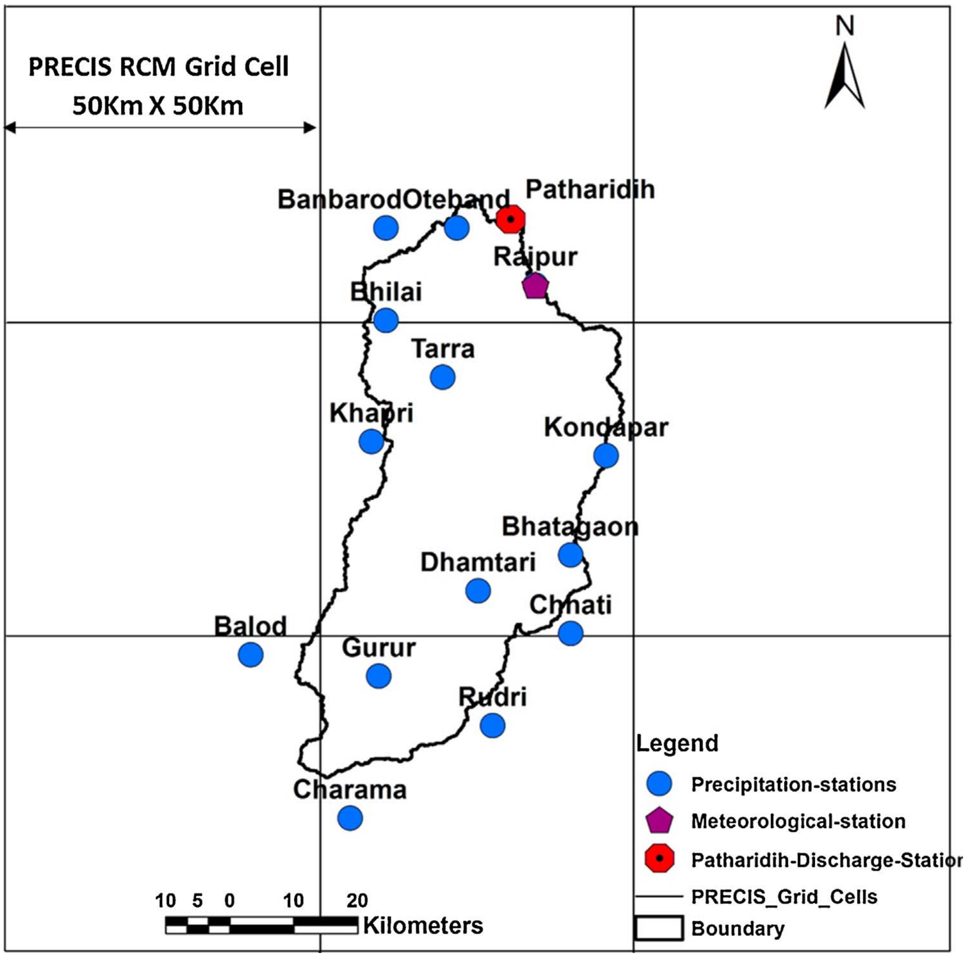


Fig. 3. Hydro-meteorological observation network of the Upper Kharun Catchment overlaid on PRECIS RCM grid cells.

from the Hadley Centre, UK. The pre-selection of three perturbed physics members results from a preliminary evaluation of all members for their ability to simulate the gross features of the Indian monsoon (Kumar et al., 2011). Continuous and long-term RCM simulations for the period 1961–2098 have been performed by the IITM. For more details see Kumar et al. (2011).

3.2. Statistical bias-correction of the PRECIS regional climate projection

The PRECIS data of the following three periods are selected for further analyses: i) 2011–2040 (2020s), ii) 2041–2070 (2050s), iii) 2071–2098 (2080s).

Kumar et al. (2011) identified substantial wet biases in model simulations over the west coast and east central India, covering the study area. These wet biases (overestimations of PRECIS precipitation compared to observations) are found to be more pronounced in the two physics ensemble members q0 and q14, whereas q1 is affected less.

To reduce the aforementioned wet biases, a statistical bias correction has been applied to the RCM grid values corresponding to the observation stations. In total, the UKC is covered by 4 RCM PRECIS grid cells of 2500 km^2 (see Fig. 3).

Since the hydrological model is calibrated based on data from 14 observation rainfall stations, bias corrected rainfall projections for the period 2011–2098 were generated for these stations. This is done by extracting the grid cell value with the closest Euclidean distance to each station, i.e. finally 42 future rainfall projections (A1 B scenario) were derived (14 stations times 3 perturbed HadCM3 physics members). For temperature only one station was used, thus 3 future projections were generated.

A simple linear scaling method for the mean values (e.g., Lenderink et al., 2007; Widmann et al., 2003; Berg et al., 2012) has been followed and applied for temperature and precipitation, which are seen to be the most crucial variables in hydrological impact assessments (e.g., Schmidli et al., 2006; Thomas, 2000). By using this simple bias correction technique, only the first order statistics are corrected, i.e. the mean values. More complex bias correction approaches exist, which are able to correct for higher order statistical moments, such as the quantile mapping approach (e.g. Panofsky and Brier, 1958; Déqué, 2007). However, statistical distribution functions must be fitted to the data in order to derive bias corrected projections for temperature and precipitation, which will introduce further uncertainties to the results. The linear scaling method has been found to reliably correct for the biases in

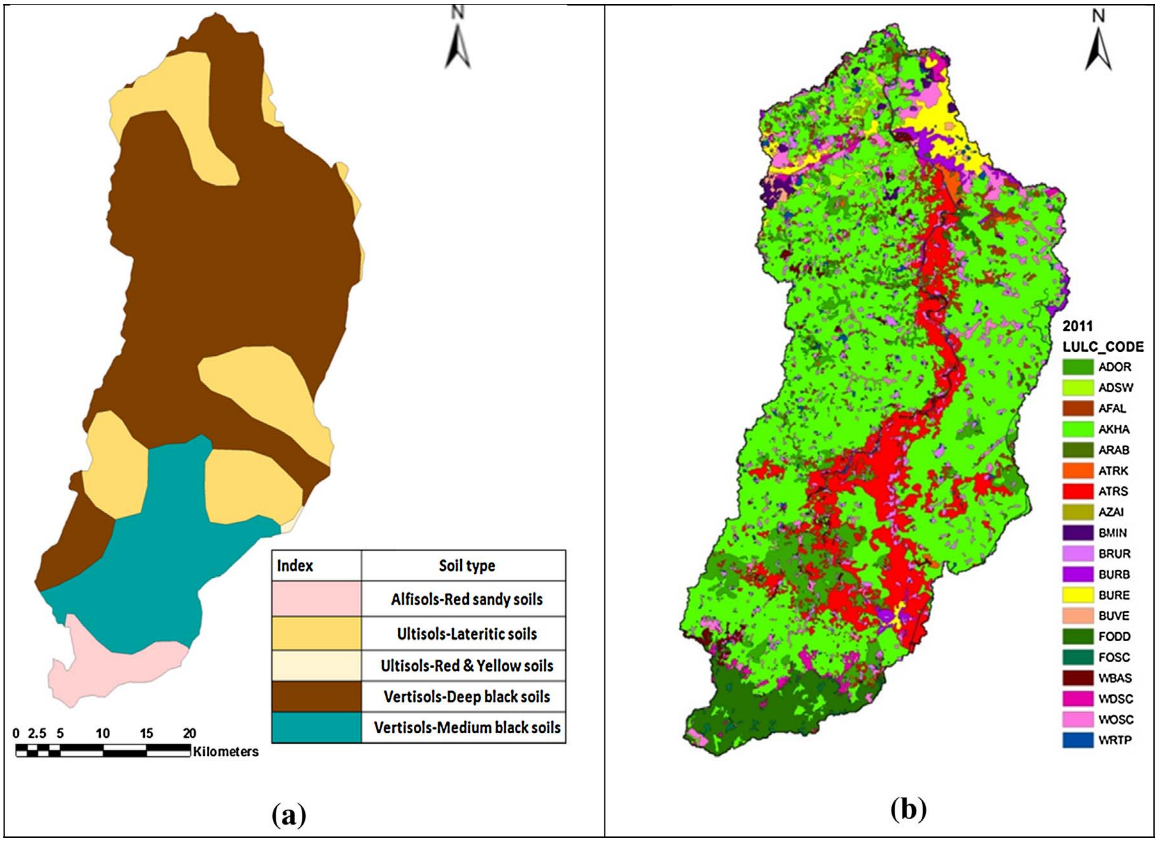


Fig. 4. (a) Soil map and (b) Land-use map (2011) of UKC.

Table 1
Detailed land-use class code definition.

SN	Land-use class code	Definition
1	ADOR	Area under crop in two-seasons (monsoon and winter).
2	ADSW	Area under crop in two-seasons (monsoon and summer).
3	AFAL	Area which are currently not used for agriculture throughout the year and left fallow.
4	AKHA	Area under crop only in monsoon season (mid July − mid November).
5	ARAB	Area under crop only in winter season (mid November − mid February).
6	ATRK	Area under crop in all the seasons with crop other than paddy in summer season.
7	ATRS	Area under crop in all the seasons with paddy as a crop in summer season.
8	AZAI	Area under crop only in summer season (mid-February − mid May).
9	BMIN	This class represents industrial areas, ashes/cooling pond/effluent/other waste and mining active area.
10	BRUR	This class comprises the rural villages with low-density settlement areas.
11	BURB	This class represents the medium density urban settlement areas and transport areas.
12	BURE	This class stands for the high-density urban settlement areas.
13	BUVE	This class covers the vegetation area near and around the urban settlements.
14	FODD	This class represents the open and dense deciduous forest area.
15	FOSC	This class consists of the degraded open deciduous forest areas.
16	WBAS	This class represents the open waste land area without vegetation. It includes exposed rocky areas, quarries and riverine sandy areas.
17	WDSC	This class comprises wasteland with dense scrubland.
18	WOSC	This class represents the wasteland with open scrubland.
19	WRTP	This class covers all surface water bodies (ponds/rivers/tanks/canals).

temperature and precipitation series in our study.

It is worth to note that it is a matter of ongoing scientific debate whether the bias correction is adding or uncovering another level of uncertainty that is related to the uncertainty induced by the choice of the GCM (Hagemann et al., 2011).

For temperature, the correction is based on an additive term and the correction function is as follows:

$$T_{corr,m}(t) = T_{mod,m}(t) + (\overline{T_{obs,m}} - \overline{T_{mod,m}}), \tag{1}$$

which is calculated for every month of the calibration period (1971–2005), where T_{corr} denotes the corrected temperature time series, and obs and mod denote the observed and modeled time series, respectively. The monthly difference between the observations and the RCM model is then added to the RCM model data at every time step t (here: daily) for the climate projection in order to generate future projections, following the seasonality of the observations.

For precipitation data, instead of using a monthly additive term as shown in equation 1, monthly ratios are calculated and applied to the PRECIS RCM projections accordingly:

$$P_{corr,m}(t) = P_{mod,m}(t).\ \frac{\overline{P_{obs,m}}}{\overline{P_{mod,m}}}, \tag{2}$$

where P_{corr} represents the corrected precipitation time series.

The calculation of the scaling values (calibration) is done for the period 1971–2005, and validated for 2006–2010 by calculating the Pearson Correlation Coefficient between monthly aggregated data. This procedure is applied to all 14 rainfall stations and one temperature station in the UKC.

3.3. Model selection: Soil Water Assessment Tool (SWAT)

The Soil and Water Assessment Tool (SWAT) was developed by Arnold et al. (1998) for the Agricultural Research Service (ARS), United States Department of Agriculture (USDA). The basic principle behind SWAT modeling is to partition a watershed into number of sub-units using a two-step approach. First, a topographic discretization is performed by dividing the watershed into a number of sub-catchments based on DEM. In the second step, the input information for each sub-catchment is grouped or organized into the following categories: climate, hydrological response units (HRUs), ponds/wetlands, groundwater and the main channel or reach draining the sub-basin. A HRU being an innovative element by SWAT represents spatial units responding similarly in hydrological terms due to a specific combination of major factors influencing hydrological processes. SWAT was selected for this research due to major features of SWAT in an advantageous way meeting the requirements of the research. Deterministic in structure, SWAT is a semi-distributed hydrological model, which is quite flexible and can be integrated with GIS. It is capable of running on a daily time step, and enables effectively stimulating hydrological processes and water balance components of medium catchments to large river basins (Arnold et al., 1998). It is freely available and has a strong network support. Basically, hydrological models face three challenges namely, deficient data, spatial heterogeneity of catchment characteristics, and the complex issues present in natural system. However, because of the semi-distributed nature of SWAT, it is able to handle all the mentioned challenges well (Gassman et al., 2007).

SWAT achieves a high level of recognition all around the world (Douglas-Mankin et al., 2010). According to Gassman et al. (2007), SWAT is known for its worldwide multi-objective applications including analyses on the impacts of climate change. It is considered as a versatile model that is flexible enough to integrate multiple environmental processes and effectively handle the watershed management practices and provide the informational base for sound policy decisions. A number of studies have been implemented so far using SWAT for simulating the impact of climate change on the hydrology of watersheds at basin scale over a long period of time (e.g., Eckhardt and Ulbrich, 2003; Githui et al., 2009; Parajuli, 2010; Stonefelt et al., 2000; Xu et al., 2008; Verbeeten and Barendregt, 2007). For India, Lakshmanan et al. (2011) analyzed the Bhavani basin and concluded that the SWAT model can be employed as a decision tool for developing adaption strategies to sustain rice production under different climate change and management projections. Gosain et al. (2006) used SWAT to investigate the climate change impact on the hydrology of Indian River basins. Dhar and Mazumdar (2009) applied the model to explore the impacts of climate change under the threat of global warming for an agricultural watershed of the Kangsabati River, India. A study on climate change response on water balance components in Krishna Basin, India using PRECIS climate projections and SWAT was carried by Kulkarni et al. (2014). They found that the SWAT model simulates the stream flow appreciably well for their study area.

In our study, based on SRTM DEM, deriving and utilizing the drainage network and river boundary as an input, SWAT delineates UKC into 29 sub-catchments and 3452 HRUs. No threshold was applied to generate the HRUs.

3.4. Analyses of climate change impact on water balance components in the UKC

The climate change impact analysis is based on the bias-corrected PRECIS RCM climate projections for the study area. Projections were developed for three different periods, i.e., the 2020s (representing the period 2011–2040), 2050s (2041–2070) and 2080s (2071–2098). The baseline period for comparison is the observed climate data of the period 1990–2008.

PRECIS provides three different climate simulations (physics ensembles q0, q1 and q14) based on the IPCC SRES A1 B scenario. These ensemble members are considered separately for the climate change impact analysis for water balance components. The change in climatic parameters indicated by PRECIS was simulated using SWAT with respect to average, wet and dry conditions in the 2020s, 2050s and 2080s in order to assess the impact of climate change projections under average conditions and scenarios representing rather wet as well as dry conditions.

For average conditions:

1. Selection of an average year (here year 2001 represents average rainfall distribution pattern in the time series for UKC)
2. With reference to 2001, extrapolation of daily rainfall and temperature values (i.e. changing the magnitude) according to the

PRECIS projections (2020s, 2050s and 2080s) for all stations (by a factor describing the ratio between projected and current representative values at monthly time steps) while keeping the temporal distribution,
3. Simulation of the water balance components with SWAT using the meteo-data of the 2001 (current/representative) and PRECIS projections 2020s, 2050s, 2080s.

For wet and dry conditions:

1. Selection of a wet year (1994)/dry year (2002) and keeping the temporal pattern of meteo-parameters, but changing the magnitude of rainfall according to PRECIS projections (same as described in for average condition),
2. Simulation with SWAT

Justification for differentiation in average, wet and dry condition: The focus of the analyses is on the average (representative) years in terms of rainfall and temperature. In addition, approximate changes of major water balance components under wet and dry conditions ('corridor' of expected impact) were also analyzed.

Basically, the purpose of the differentiation in average, dry and wet conditions comprise to (i) test the response of the hydrological model/approach on dry versus average and wet versus average situations, and (ii) clarify the tendency and estimate a range of changes (approximate a corridor of changes in hydrology (water balance components) considering wet and dry conditions). For that purpose, a semi-detailed approach was used by keeping the temporal distribution of rainfall and lowering/increasing the magnitude of rainfall according to PRECIS projections. The selection of a single (representative year) approach was applied, because PRECIS provides information on expected changes in terms of rainfall magnitude; whereas no detailed and reliable information on the changes in temporal behavior/distribution of rainfall is available (for future scenarios).

It is a fact that the temporal distribution (daily rainfall intensity) cannot be predicted and even using 30 years of simulations from a climate scenario (with expected uncertainties) yields in an average result for the time period (with an uncertain daily temporal distribution). Hence, the above mentioned semi-detailed approach based on selection of a single representative year was applied.

4. Results and discussion

This section is presenting and discussing the results in three parts: (1) sensitivity analysis, calibration and validation results of SWAT model; (2) result analysis on bias corrected PRECIS projections, and (3) impact of climate change on water balance components (considering average, dry and wet climate conditions).

4.1. Sensitivity analysis, calibration and validation of SWAT model

Fifteen hydrological parameters i.e., soil depth (SOL_Z), bio-mixing efficiency (BIOMIX), plant uptake compensation factor (EPCO), groundwater revap coefficient (GW_REVAP), soil bulk density (SOL_BD), threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN), base flow alpha factor (ALPHA_BF), deep aquifer percolation fraction (RCHRG_DP), surface runoff lag time (SURLAG), hydraulic conductivity (SOL_K), soil available water capacity (SOL_AWC), channel effective hydraulic conductivity (CH_K2), soil evaporation compensation factor (ESCO), groundwater delay (GW_DELAY) and curve number (CN2) which are based on expert knowledge were considered for the sensitivity analysis for discharge in UKC. Global sensitivity analysis method in SWAT CUP (Abbaspour, 2012) was performed for these parameters. It is found that for UKC, curve number is the most sensitive parameter followed by groundwater delay, soil evaporation compensation factor (ESCO), channel effective hydraulic conductivity, soil available water capacity, hydraulic conductivity, surface runoff lag time, deep aquifer percolation fraction

Table 2
Global sensitivity analysis of parameters.

Parameter name	t-Stat	P-Value	Ranking
R – SOL_Z(.).sol	0.00	1.00	15
V – BIOMIX.mgt	0.00	1.00	14
V – EPCO.bsn	0.04	0.97	13
R – GW_REVAP.gw	0.05	0.96	12
R- SOL_BD(.).sol	0.14	0.89	11
V- GWQMN.gw	−0.16	0.88	10
V- ALPHA_BF.gw	0.16	0.87	9
V- RCHRG_DP.gw	−0.40	0.69	8
V- SURLAG.bsn	−0.54	0.59	7
R- SOL_K(.).sol	−0.68	0.50	6
R- SOL_AWC(.).sol	0.73	0.47	5
V- CH_K2.rte	0.76	0.45	4
V- ESCO.hru	−0.93	0.36	3
V- GW_DELAY.gw	2.07	0.04	2
R- CN2.mgt	−3.18	0.00	1

Table 3
Model evaluation statistics for calibration and validation periods.

Calibration (2000–2006)	Mean (m^3/s)	R^2	NSE (Nash-Sutcliff Efficiency)
Observed	31.13	0.94	0.93
Simulated	35.45		
Validation (2007–2008)			
Observed	26.80	0.85	0.83
Simulated	32.53		

(Table 2). These 8 parameters that were found most sensitive towards generating discharge based on t-stat (multiple regression coefficient of a parameter divided by its standard error) and p-value (statistical significance) were chosen and considered for model calibration.

Calibration and Validation: The SWAT model setup was built for the period 2000–2008. The land-use map of 2010–2011 and management practices during the period were considered. The period 2000–2006 (7 year) was used for calibration and 2007–2008 (2 year) for validation, which were based on monthly streamflow discharge. The selection of different time periods for calibration and validation is due to two reasons: (i) to achieve a stable calibration; (ii) the discharge in the first period is highly variable from year to year and therefore, we included longer period than in the validation period with annual discharges rather close to average. The calibrated parameters were utilized for estimating the impacts of future climate change on water resources of UKC.

Sequential Uncertainty Fitting version 2 (SUFI 2) of SWAT CUP 2012 was applied. The uncertainty analysis routine of SUFI 2 accounts for wide sources of model parameter uncertainties and input measured data uncertainties. The goodness of model fit can be quantified by the R^2 (coefficient of determination) and/or Nash-Sutcliff Efficiency (NSE) coefficient between the observations and the final “best” simulation.

The standard deviation of observed and model simulation is close, and the R^2 and the NSE value of model calibration and validation show a good agreement between simulated and observed values (Table 3, Fig. 5). This leads to the conclusion that the model is well calibrated and validated for the study area and can be used further for impact analysis studies for the study area.

The model has performed well for average flow. However, the deviation between observed and simulated discharge under low flow conditions partly can be explained by the fact that during these periods, discharge is generated by exfiltration from groundwater aquifer. Yet, the groundwater modules in SWAT are not strictly physically based, but follow basically a storage concept and are empirically structured. Furthermore, during low-flow conditions, only limited measurements are performed. With respect to high discharge situations, we see mainly two reasons to explain the differences between observed and simulated values. Firstly, discharge measurements close to peak discharges are only possible with a rather limited precision (contribution of the floodplain to the discharge in the river; limited options for velocity measurements). Secondly, daily time-steps in SWAT (rainfall, discharge) limit the achievable precision of the simulations, because intra-daily variations in rainfall intensity might by influential on discharge generation, but are not monitored by the rainfall stations (at hourly time steps) and not sufficiently considered in SWAT (temporal resolution).

4.2. Bias correction of PRECIS climate projections

Fig. 6 shows exemplarily the results of the bias correction of the PRECIS RCM (A1 B scenario, q0 physics member) for rainfall at station Raipur. In an analogous manner, the bias correction was performed for all 14 stations as well as the other two available physics ensemble members q1 and q14.

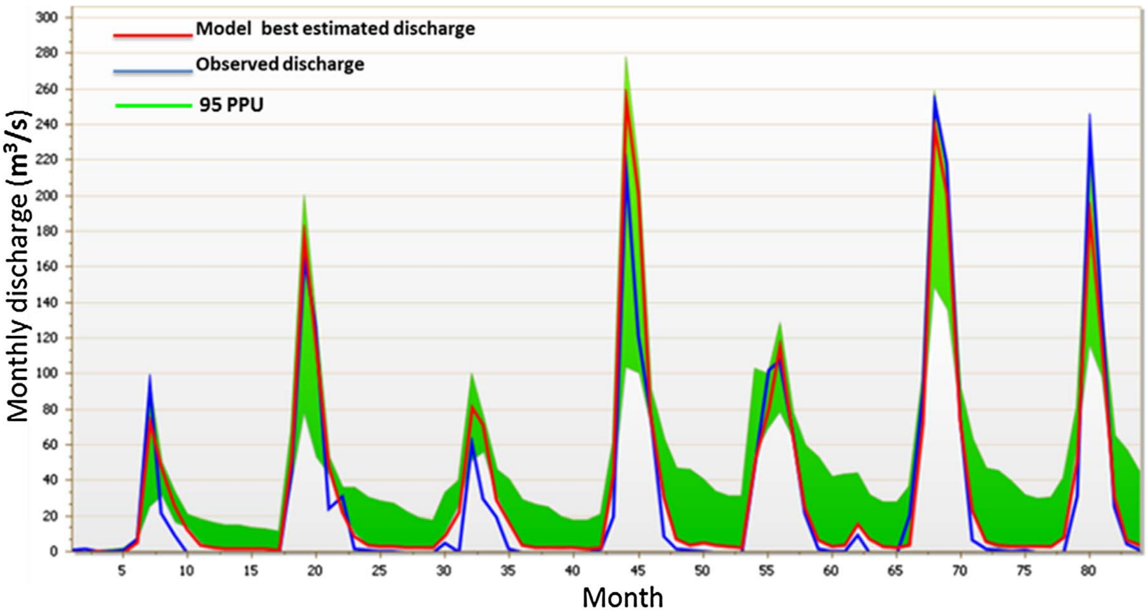
The PRECIS physics member q0 shows significant wet biases compared to the rainfall observations at Raipur. For every month, there is a tendency of PRECIS to over-estimate rainfall values (only positive scaling factors are found). The highest biases in terms of the absolute values are observed during the monsoon (June to September), however, the highest scaling was performed during the dry season (January and February).

The derived monthly scaling factors of the calibration period were applied to the RCM for an independent validation period (2006–2010). A Pearson correlation coefficient of 0.83 (monthly rainfall values at Raipur) was found. The same scaling factor was subsequently applied to obtain bias corrected rainfall projections (based on A1 B emission scenario and the physics ensemble members q0, q1, and q14) for the period 2011–2098, i.e. pseudo observations at the 14 locations used for the SWAT calibration.

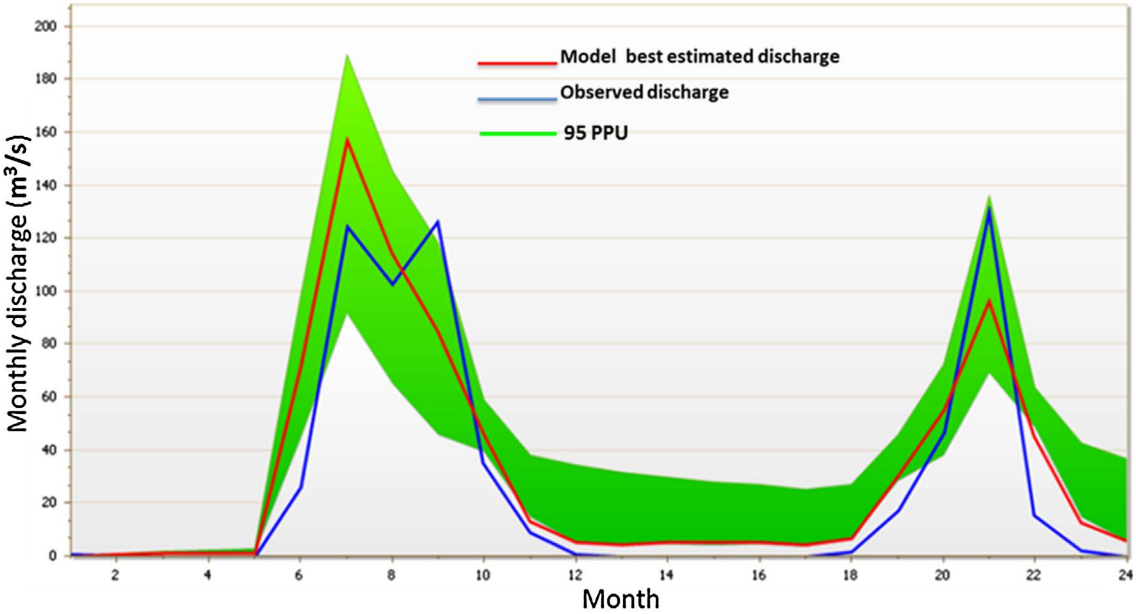
4.2.1. PRECIS rainfall statistics for Upper Kharun catchment

The 14 rainfall stations were bias corrected following the method presented above. The validation results were quite acceptable with correlation coefficients of larger than 0.8 in most of the cases. In order to derive a rainfall value representative for the UKC, observations from the 14 rainfall stations were weighted using the nearest distance to centroid approach. Each delineated subbasin in the SWAT model receives the rainfall values from the gauge that is nearest to its centroid. The UKC rainfall for the bias-corrected q0, q1 and q14 PRECIS projections were analysed against the measured baseline mean monthly values (Table 4).

For q0 rainfall projection: based on the results, it is concluded that the mean annual rainfall for the UKC compared to the baseline (mean annual observed values, 1990–2008) will slightly decrease by 10 mm (0.9%) in the 2020s, increase by 202 mm (18.2%) in the 2050s, and further increase by 323 mm (29.1)% in the 2080s.



(a)



(b)

Fig. 5. Comparison between simulated and observed mean monthly streamflow for the (a) calibration period (2000–2006) and (b) validation period (2007–2008).

For q1 rainfall projection: compared to the baseline period, there is a significant decrease of 136 mm (12.3%) rainfall for the 2020s, a decrease of 74 mm (6.7%) for the 2050 s and an increase of 128 mm (11.5%) for the 2080s.

For q14 rainfall projection: in comparison with the baseline period, there is a clear increase of 127 mm (11.4%) rainfall for the 2020s, an increase of 80 mm (7.2%) for the 2050 s and an increase of 227 mm (20.5%) for the 2080s.

The PRECIS future climate projections feature wide variations in rainfall projections. The q1 projection shows a decreasing trend for rainfall in the 2020 s and 2050s, while q0 and q14 lead to an increasing trend for the same period. In all projections, a decrease of rainfall in June is expected (Table 4).

Considering the average of q0, q1 and q14 scenarios and comparing it with baseline shows an annual rainfall decrease by 0.6% for 2020s; an increase in annual rainfall by 6.2% for 2050 s and an increase by 20.4% annual rainfall by 2080s.

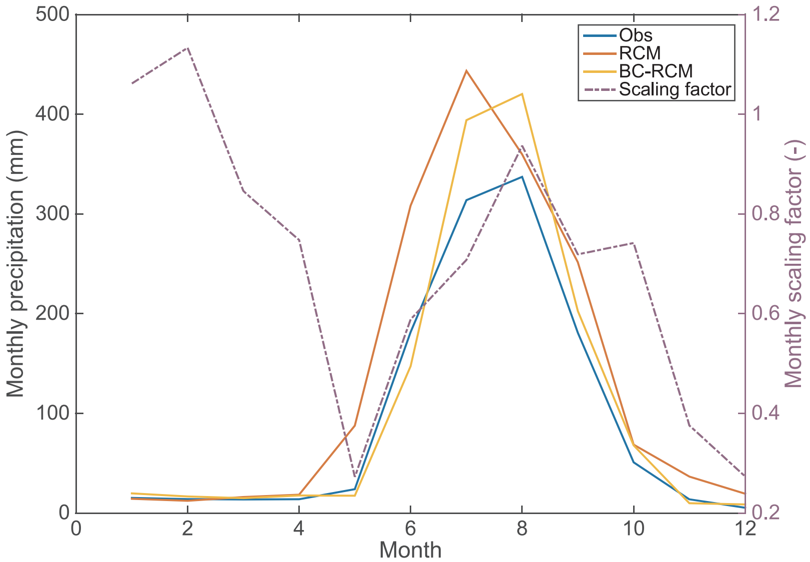


Fig. 6. Bias correction of the PRECIS rainfall (q0, A1B), exemplarily shown for Raipur station. The calibration of the bias correction between observed (blue) and RCM (red) is performed for the period 1971–2005 to derive monthly scaling factors (purple), which are then used to scale the RCM projection for the period 2011–2098 (yellow). The Pearson correlation coefficient between observed and modeled rainfall on monthly time scale is r = 0.83 for the independent validation period 2006–2010. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Percentage change in rainfall in different PRECIS projections and time horizons compared to baseline.

Precipitation													
UKC	Baseline (1990–2008)	2020s				2050s				2080s			
Month	Amount (mm)	q0	q1	q14	Avg.	q0	q1	q14	Avg.	q0	q1	q14	Avg.
Jan	3.3	−22.5	5.8	−23.4	−13.4	13.1	110	4	42.4	6.4	91.8	22.5	40.2
Feb	0	0	0	0	0.0	0	0	0	0.0	0	0	0	0.0
Mar	9.4	−18.5	59.8	−10.4	10.3	6.7	7.3	−13.6	0.1	−24.7	−1	11.4	−4.8
Apr	11.6	8.7	−8.7	28.8	9.6	−10.5	−4.9	1.3	−4.7	1.5	−32.9	17.9	−4.5
May	8	−22.7	6.8	17.9	0.7	15.4	−18.4	−35.9	−13.0	−30	−2.5	19.1	−4.5
Jun	360.1	−27.9	−20.6	−3.7	−17.4	−3.8	−38.8	−13.3	−18.6	−29.2	−7	−29.4	−21.9
Jul	352.5	6.3	−12.2	29.4	7.8	35.7	4.5	19	19.7	63.9	36.5	42.5	47.6
Aug	244.8	17.2	−6.2	−2.1	3.0	34.5	15.2	18.2	22.6	69.4	10.4	39	39.6
Sep	62	−1.5	−22.8	10.4	−4.7	−9.7	−6.9	3.8	−4.2	7.1	−7.6	26.8	8.8
Oct	56.1	55.8	7.8	57.5	40.4	18.6	23.8	30.2	24.2	59.9	10	109.9	59.9
Nov	2.4	−35.6	22.6	−13.8	−8.9	−9.6	43.1	37.7	23.7	−13	−19.7	179.5	49.0
Dec	0	0	0	0	0.0	0	0	0	0.0	0	0	0	0.0
Annual	1110.2	−0.9	−12.3	11.4	−0.6	18.2	−6.7	7.2	6.2	29.1	11.5	20.5	20.4

4.2.2. PRECIS temperature statistics for Upper Kharun catchment

1 *Annual mean of daily maximum temperature*:

For the q0 maximum temperature projection: the mean annual maximum temperature for the Raipur UKC compared to the baseline (observed values, 1971–2005) will increase by 1.5 °C for the 2020s, by 2.5 °C for the 2050s and by 3.7 °C for the 2080s.

For q1 maximum temperature projection: the mean annual maximum temperature for the UKC compared to the baseline (observed values, 1971–2005) will rise by 1.1 °C for the 2020s, by 2.5 °C for the 2050 s and by 3.6 °C for the 2080s

For q14 maximum temperature projection: the mean annual maximum temperature for the UKC compared to the baseline (observed mean annual maximum temperature values, 1971–2005) will increase by 1.1 °C for the 2020s, by 3.0 °C for the 2050s and by 3.5 °C for the 2080s.

All projections (q0, q1 and q14) are in agreement with respect to an increasing trend of the mean monthly maximum temperature of all months compared to the baseline projections.

Range of maximum temperature increase considering q0, q1 and q14 projections together (average), compared to baseline for 2020s will be between 1.1 and 1.5 °C, for 2050 will be 2.5 and 3.0 °C and for 2080s it will increase between 3.5 and 3.7 °C.

2 *Annual mean of daily minimum temperature*:

For q0 minimum temperature scenarios: The mean annual minimum temperature for the UKC based on q0 compared to baseline will increase by 2.0 °C for the 2020s, by 3.6 °C for the 2050s and by 6.7 °C for the 2080s.

For q1 minimum temperature projections: Regarding the q1 minimum temperature projections, it can be concluded that the mean annual minimum temperature for the UKC compared to the baseline will increase by 1.4 °C for the 2020s, 2.8 °C for the 2050 s and 4.0 °C for the 2080s.

For q14 minimum temperature projections: According to the q14 minimum temperature projections, the mean annual minimum temperature for the UKC compared to the baseline will increase by 1.4 °C for the 2020s, 3.3 °C for the 2050 s and 4.5 °C for the 2080s.

It was found that the mean monthly minimum temperatures of all months in q0, q1 and q14 are increased compared to the baseline projection. Range of minimum temperature increase considering q0, q1 and q14 projections together (average), compared to baseline for 2020s will be between 1.4 and 2.0 °C, for 2050s it will range between 2.8 and 3.6 °C and for 2080s it will be 4.0 and 6.7 °C. According to the considered projections, the mean annual minimum temperature is increasing more than the mean annual maximum temperature.

4.3. Impact of PRECIS climate change projections on the water balance components of UKC

The impact of climate change projections on water balance components in terms of discharge, surface runoff, percolation, actual evapotranspiration, groundwater contribution to streamflow was analysed at two different levels: (1) considering PRECIS average climate condition; (2) based on PRECIS average, wet and dry conditions (taking into account only q1 projection);

The impacts of the average climate situation on the water balance components were discussed in detail, while the impacts in years representing wet (high) and dry (low) rainfall conditions were discussed in terms of runoff-rainfall ratios and with respect to changes in surface runoff and percolation only (as an example, these analyses were performed only for the ensemble member q1, because it was found to be less biased in our study region (Kumar et al., 2011)).

4.3.1. Impact of climate change under average climate condition

The impact of PRECIS climate projections (under average climate condition) on water balance components in percentage changes compared to the baseline projections are presented and discussed in this section. It is evident that the amount of rainfall is significantly high in monsoon season compared to the rest of the months. Hence, a small percent change in water balance components in monsoon season represents a big change in the magnitude of water balance components whereas a big percentage change in rest of the season will reflect a small change in amount (Figs. 7–10). In addition, even small changes in rainfall during the monsoon period potentially have a high impact on runoff, because in the monsoon period, the soil moisture is rather high (close to field capacity) which is a critical soil moisture characteristic strongly influencing partitioning of rainfall into infiltration or surface runoff. In the non-monsoon season, soil moisture is rather low and therefore changes in rainfall do not very much impact runoff (additional rainfall in tendency is kept in the soil storage and not partitioned into surface runoff or percolation).

Precipitation (mm): Already discussed above in section 4.2.1 (Table 4, Fig. 7a–d)

Discharge (m3/s): For the 2020s and 2050s, the simulations indicate opposite trends of discharge compared to the baseline depending on the PRECIS projection used. For the 2020s, simulation results show an average annual decrease by 2.9% (varies

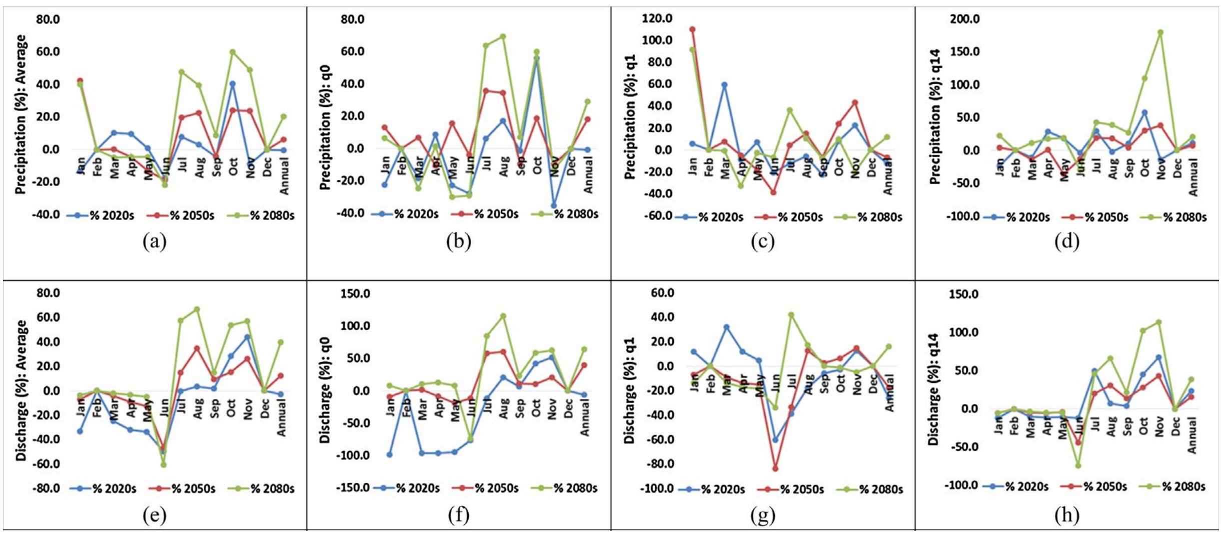


Fig. 7. (a-ab). Impact of PRECIS climate projections (average of projections and q0, q1 and q14) considering average climate condition on percentage changes in water balance components at time steps 2020s, 2050 s and 2080s.

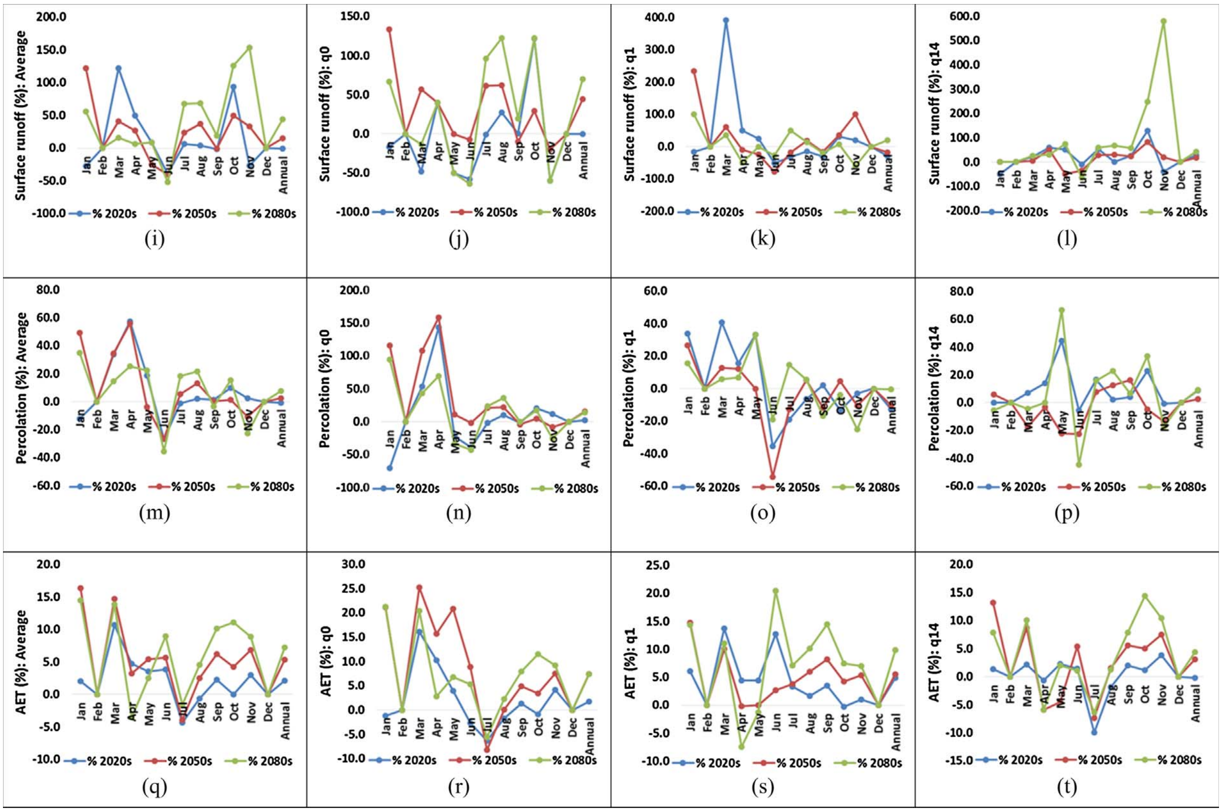


Fig. 7. (*continued*)

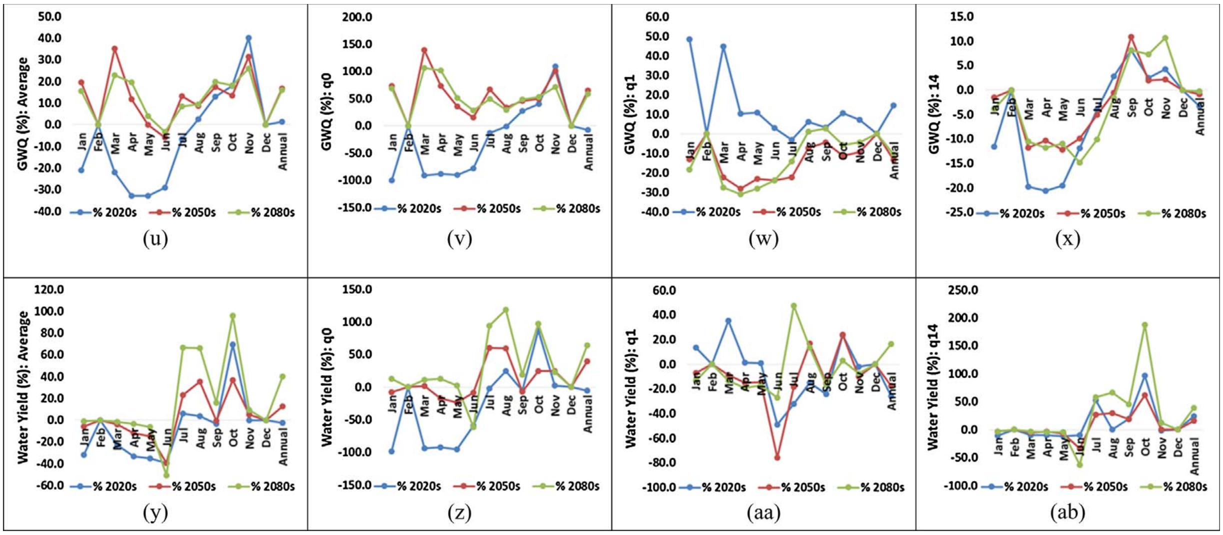


Fig. 7. (*continued*)

between a decrease by 25.9% for q1 to an increase by 23.6% for q14), and for the 2050s results show an average annual increase by 12.4% (range from 17.6% decrease (q1) to a 39.4% increase (q0)). The simulations of 2080s agree on an average annual increasing trend by 39.5% (in the range of 16.3% (q1) to 63.7% (q0) increase) (Fig. 7e–h).

Surface runoff (mm): Depending on the PRECIS projection, simulations on surface runoff lead to opposite trends of surface runoff in the 2020s and 2050s. As surface runoff is the main contribution to discharge, a similarity with the discharge pattern (see above) can be observed. For the 2020s, surface runoff shows an average annual decrease by 0.7% (in the range of 28.8% decrease (q1) to 26.8% increase (q0)). For the 2050s, the projections lead to an average annual increase by 14.6% (varying between 17.9% decrease (q1) to 44.1% increase (q0)), and for the 2080s all projections lead to an increasing trend in the range of 19.5% (q1) to 69.6% (q0) with an annual average increase by 44.1% (Fig. 7i–l).

Percolation (mm): For the 2020s, average annual percolation is found to decrease by 0.8% (in the range of 12.8% decrease to 8.7% increase) compared to the baseline. Projections for the 2050s show an average annual increase by 2.5% (varying between 10.3% decrease and 15.4% increase), and for the 2080s an annual average increase by 7.5% (ranging from 0.3% decrease to 13.7% increase). Projection q1 shows a decrease in all the time steps compared to the baseline (Fig. 7m–p).

Actual evapotranspiration (mm): An increase in actual evapotranspiration (AET) is simulated in all projections for different time steps except for the q14 projection with respect to the 2020s where a very slight decrease is achieved. Compared to the baseline, the expected changes in the AET vary between a very slight decrease by 0.2% and a 4.86% increase with an average annual increase by 2.1%. For the 2050s and 2080s, the projections show an increasing trend of 3.1% to 7.4% (with an average annual increase by 5.3%) in the 2050s and 4.3% to 9.8% (with an annual average increase by 7.2%) in the 2080s. The least increase is for the q14 projection, while q1 features the highest increase (Fig. 7q–t).

Groundwater contribution to streamflow (mm): Projections on the groundwater contribution to streamflow strongly depend on the PRECIS projection as indicated by different trends compared to the baseline. For the 2020s, annual groundwater contribution to streamflow is in the range of 7.0% decrease to 14.7% increase (with an average annual increase by 1.5%). The simulations for the 2050s predict 13.3% decrease to 64.7% increase (with an average annual increase by 16.9%), and for the 2080s the range is 10.4% decrease to 59.1% increase (with an average annual increase by 16.1%). q1 leads to a decrease in all the time steps compared to the baseline (Fig. 7u–x).

Water yield (mm): It is the total amount of water leaving the HRU and entering main channel during the time step (Water Yield = Surface Runoff + Lateral Flow + Groundwater Contribution to Streamflow − Transmission Loss − pond abstractions). As water yield is dominated by surface runoff and discharge, the pattern of projected changes is similar. Compared to the baseline, the annual water yield is in the range of 26.0% decrease to 23.8% increase (with an average annual decrease by 2.5%) for the 2020s. For the 2050s, a 17.4% decrease to 39.9% increase is simulated (with an average annual increase by 12.8%), and for the 2080s, the projections follow this increasing trend with magnitudes ranging from 16.7% to 64.5% (with an average annual increase by 40%). Compared to the baseline, q14 shows an increase in all time steps (Fig. 7y, z, aa, ab).

Fig. 7 contains and visualizes the full information on changes in the major water balance components driven by climate change projections as simulated by SWAT (referring to average rainfall conditions). For the considered climate change projections (q0, q1, q14) and regarding the time-periods (2020s, 2050s, 2080s), the impact (relationship) of expected alteration in rainfall on any of the water balance components can be assessed by pairwise comparison of the respective parts in Fig. 7 (see: examples given below). This provides the starting-point for conceiving water management measures to counterbalance disadvantageous changes in the water balance components (more on the concepts: see Chapter on Conclusions).

In the following section, we focus on some examples regarding the impact (relationship) of climate change (mainly: altering rainfall) on water balance components which we consider especially relevant for future water management concepts (besides the rather obvious assessment on rainfall as dominating factor in (1)); (2) rainfall change and surface runoff (relevant as increasing runoff may lead to higher flood risks); (3) rainfall change and percolation (percolation recharges groundwater and needs therefore to be considered as a limit for sustainability groundwater use), (4) changes in actual evapotranspiration (influential on future irrigation demand being already the biggest water user). We consider the influential period of the monsoon.

(1) The rainfall pattern of the climate projections is clearly the dominating impact on water balance components in the study area
(2) The surface runoff reacts in an over-proportional pattern to changes in rainfall (as an example: Fig. 7 a depicts an increase in rainfall during the monsoon months July and August for the 2080s of around 40% which leads to an increase in surface runoff by around 60% as shown in Fig. 7 i). As surface runoff contributes strongly to discharge in flood periods, the over-proportional relationship necessitates further analyses in order to assess the magnitude of an increasing flood risk and to conceive counter-balancing infrastructural and management options.
(3) The relation between rainfall changes and the effect on percolation shows an opposite behavior. High increases in rainfall yield only in rather small rise in percolation (for example: the above mentioned 40% increase in rainfall in the 2080s projection (Fig. 7a) leads only to rise in percolation by 20% (Fig. 7m). With respect to water management, the under-proportional reaction of percolation on rainfall changes leads to a limit for increasing groundwater withdrawals in order to ensure sustainability in long-term use of that valuable resource).
(4) An upward trend in actual evapotranspiration in tendency leads to higher irrigation demand. As a consequence, re-arrangements in irrigation management towards higher irrigation efficiencies and more appropriate irrigation schedules should be further evaluated. Especially the non-monsoon periods deserve special attention, because higher irrigation demand (plus rises in demand of further water users (domestic, industry, ecosystem service)) may enhance groundwater withdrawals, which is critical and might lead to over-exploitation because recharge is limited due to an under-proportional increase of percolation.

Historical data on discharge measurements are available at the outlet of UKC since 1989. An analysis on the relationship between runoff-rainfall coefficient and rainfall reveal a clear increase of the coefficient with higher rainfall. This supports the over-proportional rainfall − surface runoff relationship which was simulated by SWAT and is visualized in Fig. 7.

4.3.2. Impact of PRECIS q1 climate projection based on average, wet and dry conditions on precipitation, surface runoff and percolation

Out of the scenarios under consideration, q1 scenario shows best agreement with the climate of the study area for the baseline period. Kumar et al. (2011) also advocates that for Chhattisgarh state (the study area is a part of this state) q1 scenario has less biases

Table 5
Runoff-rainfall ratio for PRECIS average, wet and dry conditions.

Average condition											
Baseline	q0 projections			Baseline	q1 projections			Baseline	q14 projections		
1990–2008	2020s	2050s	2080s	1990–2008	2020s	2050s	2080s	1990–2008	2020s	2050s	2080s
0.39	0.37	0.46	0.50	0.39	0.33	0.35	0.41	0.39	0.44	0.42	0.45
Wet condition											
Baseline	q0 projections			Baseline	q1 projections			Baseline	q14 projections		
1990–2008	2020s	2050s	2080s	1990–2008	2020s	2050s	2080s	1990–2008	2020s	2050s	2080s
0.57	0.56	0.63	0.66	0.57	0.52	0.55	0.59	0.57	0.61	0.60	0.63
Dry condition											
Baseline	q0 projections			Baseline	q1 projections			Baseline	q14 projections		
1990–2008	2020s	2050s	2080s	1990–2008	2020s	2050s	2080s	1990–2008	2020s	2050s	2080s
0.26	0.26	0.35	0.40	0.26	0.20	0.24	0.30	0.26	0.31	0.29	0.34

in rainfall compared to the q0 and q14 scenarios. Hence, q1 scenario is used to study the impact based on average, wet and dry conditions on precipitation, surface runoff and percolation. As argued more detailed in section 3.4, the major reason for expanding the simulations from only considering average conditions to taking a wet and a dry scenario into account is the intention to provide a ‘numerical corridor’ of future changes in water balance. Furthermore, this exercise enables to assess the behavior of the model.

The hydrological reaction simulated by SWAT (in terms of discharge) on altering rainfall is over-proportional. This is indicated by higher runoff-rainfall ratios for the projections reflecting wetter rainfall conditions and by lower ratios under dry scenarios. As depicted in Table 5 all ratios for wet are higher and all rations for dry conditions are lower than the respective ones in the average situation. A comparison across the projections reveals that the SWAT simulations produced similar runoff-rainfall coefficients for similar range of rainfall. For example the projection qo for the 2080s (with a rainfall of 1433 mm) yields to a coefficient 0.50 which is very close to the results of the simulation q1 regarding 2020 s with 1416 mm rainfall and a coefficient of 0.52. Furthermore, bringing all the simulations together reveals a very clear and close correlation between rainfall and simulated runoff-coefficients. This supports plausibility of the SWAT simulations.

Measurements of discharge at the outlet of the UKC are performed daily since 1989 by monitoring of flow velocity and water level from which rating curves can be established and applied. Calculating runoff-rainfall coefficients from these measurements and comparing years with different magnitudes of rainfall indicate a clear over-proportional increase of the runoff-rainfall coefficients with higher annual rainfall. Under-proportional behavior towards lower rainfall can be also observed from the comparison, but not as distinct as over-proportional feature with increasing rainfall. This might be due to intra-daily rainfall intensity which is below the resolution by rainfall stations. Yet, the over- (and under)-proportional relation between runoff and rainfall in the historical data is in-line with the simulation results achieved by SWAT.

Figs. 9 and 10 complement Fig. 8 (referring to the average conditions) by introducing a wet (Fig. 9) and a dry scenario (Fig. 10). Comparing the scenarios leads to following assessments:

(1) The surface runoff and the percolation are clearly driven by changes in rainfall (Figs. 8–10).
(2) Yet, the magnitude of the effect is high in terms of surface runoff (see for example: bars showing the surface runoff for the time-periods 2020s, 2050s, 2080s) at parts (b) of Figs. 9 and 10 showing stronger numerical changes as in the rainfall bars for respective time-periods (parts a) of the Figures which is indicating an over-proportional runoff-rainfall reaction and very low for

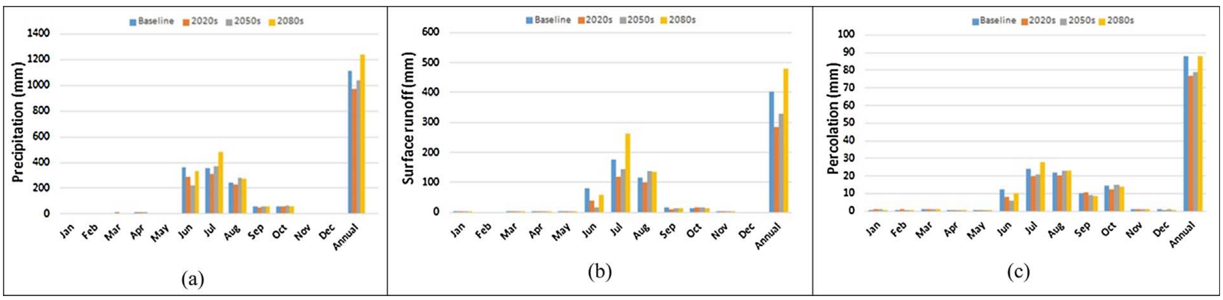


Fig. 8. Average condition: PRECIS q1 projection impact on changes in absolute magnitude of (a) precipitation, (b) surface runoff, and (c) percolation.

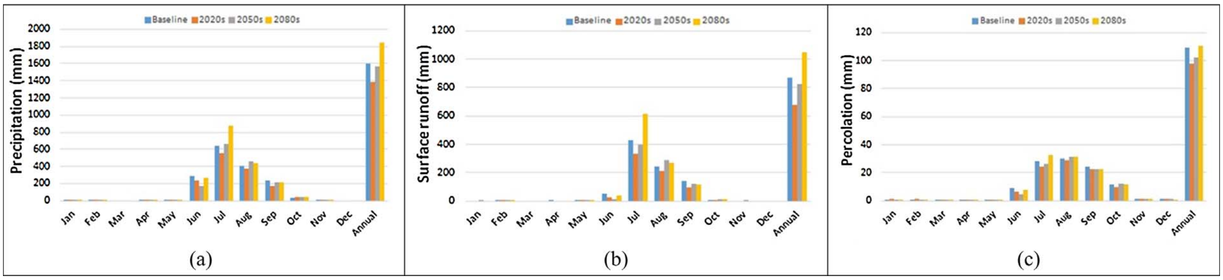


Fig. 9. Wet condition: PRECIS q1 projection impact on changes in absolute magnitude of (a) precipitation, (b) surface runoff, and (c) percolation.

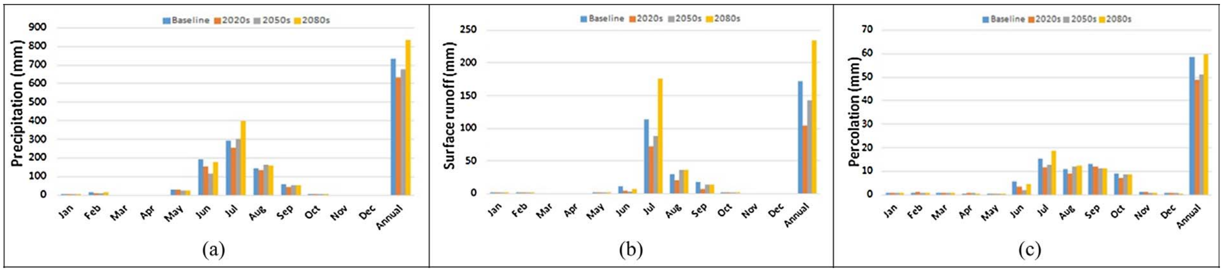


Fig. 10. Dry condition: PRECIS q1 projection impact on changes in absolute magnitude of (a) precipitation, (b) surface runoff, and (c) percolation.

percolation (indicated by rather small differences in percolation bars for 2020s, 2050s and 2080s in parts c) of the Figures.

(3) The results in terms of surface runoff and percolation simulated for wet and dry scenarios indicate an approximation regarding a ‘numerical corridor’ on expected changes in these important water balance components. The corridor is given by the bars on runoff for wet and dry conditions (related to a specific time-period); in an analogous way for percolation.

Conclusions on how to utilize these findings as well as on further needs towards more detailed analyses are given below.

5. Conclusions and recommendations

In a first section of this chapter, conclusions on the impact of climate change on the water balance from the model-based simulations are drawn. This provides the base to derive recommendations towards water management and further study needs given in the second part of the chapter.

(i) The rainfall pattern of the climate projections is clearly the dominating impact on water balance components in the study area.
(ii) As the simulation results lead to an increasing runoff coefficient with an increasing rainfall, a rather high increase in discharge can be expected which will enhance the risk of floods in low lying areas, whereas the recharge (via percolation) remains nearly constant.
(iii) The high uncertainties of expected changes in rainfall (marked differences in the PRECIS projections) are translated into high uncertainties in the simulated changes of discharge and further water balance components.
(iv) Driven by the projected temperatures, the actual evapotranspiration shows increasing trends. The magnitude of the trends depends on the PRECIS projections.

With respect to the strong effect of the projected increase in rainfall on surface runoff and low effect on percolation, the following conclusions for water management and need for as well as direction of further studies are drawn from our research:

(i) Additional facilities and strategies to increase the storage capacity of the landscape should be considered. Respective concepts could combine technical facilities (reservoirs, infiltration sites) and land management practices towards enhancing landscape storage. Conceiving decentral interventions (in addition to central options providing the ‘backbone’ of the concept) enables a close match of spatially different needs for increased storage and allows to adapt the measures depending on more reliable information gained in future or answering future changes.
(ii) It is recommended to carry out more detailed runoff-rainfall analyses with higher temporal resolution in order to assess a potentially increase of flood risks (as our simulations show an over-proportional reaction of runoff on higher rainfall).
(iii) As recharge is projected to remain nearly constant (despite increase in rainfall), whereas at least in parts of the catchment the groundwater withdrawals for intensifying cropping pattern especially in the non-monsoon seasons are expected to increase and, as a consequence, the risk of over-exploitation needs to be considered and counterbalanced by management measures. These measures could start with intensified monitoring systems in order to detect ‘hotspots’ areas (sites with high groundwater

withdrawals contrasting insufficient recharge ratios leading in tendency to overexploitation of groundwater and thus threatening its sustainability) and may direct implementation of economic incentives − dis-incentives systems, and eventual institutional arrangement (restrictions) with high priority to the detected 'hotspot sites'.

(iv) An increasing trend in actual ET in combination with an observed process on expanding and intensifying irrigation in the UKC create the need to carry out more detailed analyses on the impact of irrigation on surface and groundwater resources.

The changes in water balance components (and their magnitude) are a result of the interplay between climate change and land-use changes. As a consequence, the impact of climate change in a given basin depends on the land-use in the specific basin. Use of advanced information on climate change projects needs to go hand-in hand with high resolution in considering the land-use. The detailed land-use maps derived in this study are a promising step towards enabling a sound estimation of the climate change impact. This can be seen as an innovative feature and an advantage in terms of the methods in this study and especially in regarding the application in the Upper Kharun basin. A further advantage of the detailed consideration of the land use type, crop rotation and irrigation amount while estimating the impact of climate change is the option to conceive targeted recommendations on land use management which are appropriate to counterbalance the impact of climate change on the water balance. This effectively can support water management, especially while aiming at an integrated approach (IWRM). Taking a pragmatic perspective, it can be stated that there is a wide gap between availability of detailed research performed on the impact of climate change on water resources for the study area and the urgent need for respective information in order to conceive adaptive water management strategies in time.

Our study has the potential to contribute to bridge that gap and improve the information and knowledge base to effectively support decision makers aiming at sustainable water management. This refers directly to the Kharun catchment, but indirectly to comparable catchments due to above-mentioned advantages in methodological terms.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ejrh.2017.07.008.

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